(Non)cogs in the Wheel: Early Noncognitive Traits and High School Graduation

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Abstract

Though the relationship between so-called noncognitive traits and high school graduation is well established, few studies seek to understand this relationship using early measures of noncognitive traits (before sixth grade). Such an approach reflects a theoretical perspective of dropout as a process, rather than an event. This study offers opening insights into this relationship using data from the Child Development Supplement and Transition to Adulthood portions of the Panel Study of Income Dynamics. Methodological considerations, including approaches to extreme missingness and the operationalization of noncognitive traits, are also addressed. The analysis finds that, measured at this early age, noncognitive traits are more predictive of high school graduation than cognitive skills when controlling for demographic characteristics. The study does not uncover causal mechanisms or subpopulation-specific effects of noncognitive traits. It demonstrates the value of conceptualizing dropout as an event, rather than a process, and suggests areas for future research.

Introduction

High school graduation is an important outcome for both society and individuals. Economically, secondary educational attainment in the United States has been cited as one of the crucial elements contributing to the economic growth of the United States in the twentieth century (Aaronson and Sullivan 2002; DeLong, Goldin, and Katz 2003). At an individual level, although real wages have declined, the returns to completing high school have grown significantly, even, some argue, surpassing the returns to finishing college (Autor, Katz, and Kearney 2005; Heckman, Lochner, and Todd 2008). High school graduation also provides a pathway to further educational attainment.

The effects of high school graduation are not purely economic. There is a broad base of literature associating educational attainment with a variety of socially and individually desirable outcomes. Educational attainment is strongly related to civic engagement, and high school dropouts tend to vote at significantly lower rates than the more highly educated (see Coley and Sum (2012) for a recent finding supporting this well-documented phenomenon). They also exhibit anti-social behavior like criminal activity at higher rates, a pattern that has been documented for more than one hundred years (for a somewhat recent analysis of education amongst the incarcerated population in the United States, see Harlow (2003)). It is a well documented (though less well understood) phenomenon that educational attainment is positively associated with better health outcomes, both in terms of self-reported health status and mortality rates (see Ross and Wu (1995) for an excellent, albeit slightly dated, review of the literature). Although it is unclear that increasing the high school graduation rate would directly influence these outcomes at a broader level, it remains important to understand the processes common to all of these outcomes.

One may reasonably ask why it is important to study high school graduation now, at a time when the National Center for Education Statistics reports at least fifteen years of steadily declining high school dropout rates. One argument is moralistic. In a society where economic opportunity operates largely through educational attainment, some argue that it is not justifiable to allow anyone to fall through the cracks. This argument holds particular sway when also considering the unequal dropout rates among social groups (see, for example, Aud and Wilkinson-Flicker (2013)). In this view, high school graduation serves as a systematic sorting mechanism perpetuating existing social order.

Another response is less lofty: the official statistics may simply be misleading. Heckman and LaFontaine (2007), for example, argue that by counting General Educational Development (GED) and other high school equivalency earners as high school graduates, the National Center for Education Sciences report dropout rates in ways that fail to reflect changes that are meaningful to the efficiency of the American labor force. Cameron and Heckman (1993) find that GED holders meet economic fates more similar to high school dropouts than high school graduates. When taking this into account, Heckman and LaFontaine (2007) find that high school graduation rates have actually *decreased* among those born in the United States in the same time period. From either viewpoint, though, high school graduation is an important outcome worthy of study.

High school graduation literature

There is a truly voluminous body of research seeking to understand specifically the factors that predict high school dropout. These studies employ a variety of analytical methods, from qualitative case study to statistical analysis based on national and local datasets. Because even the most complex statistical models make causal conclusions tenuous, it is most appropriate to discuss this literature as exploring the factors that predict, or are associated with, high school dropout.

An excellent, up-to-date, and extensive review of the empirical literature can be found in Rumberger and Lim (2008). I here provide only a very brief overview of the relevant findings. In Noncognitive Traits and High School Graduation, I explore more extensively the previous literature on the topic of this paper.

Predictors of high school graduation can be categorized into those that focus on individual-level predictors, and those that focus on institutional predictors.

The first, individual-level predictors, can be further broken down into educational experience, behaviors, attitudes, and background. Perhaps unsurprisingly, the most commonly studied area is educational experience. The majority of studies find statistically significant effects of high school and middle school academic performance, measured both through test scores and grades (Rumberger and Lim 2008). The relative age of a student with respect to his or her class is also predictive. Both behaviors and attitudes overlap with noncognitive traits, which are discussed below. Finally, background demographic factors play a decidedly important role in shaping outcomes, although statistical significance is highly sensitive to the controls employed (Rumberger and Lim 2008).

Outside of individual predictors, social scientists often focus on the way institutions can shape dropout outcomes. Characteristics of the family, including structure, resources (financial, social, and cultural), parental education levels, and parental expectations, are associated with graduation outcomes. There is also evidence that characteristics of schools, particularly student socioeconomic composition pupil-teacher ratios shape outcomes of the students within them (Rumberger and Lim 2008).

As I imply in this brief overview, much of the high school graduation literature focuses on predictors that immediately precede drop out. Such a limited perspective is clearly unsatisfactory, as the circumstances that culminate in life events like high school graduation consist of a long series of reciprocal interactions between individuals and their external environments that continually shape and reshape their opportunities and path. In this sense, warning factors can, and do, emerge early, and it is at these early stages that subtle interventions can drastically shape future outcomes. Because much of this process takes place in the institutionalized setting of school, it is logical to focus on the early stages of formal schooling: primary and elementary schools. Yet the scholarship on these early predictors is not well developed.

Some scholars have investigated the effects of early educational experience. Most, but not all, studies find early test scores to be insignificant predictors of high school graduation after controlling for demographic characteristics (Alexander, Entwisle, and Horsey 1997; Alexander, Entwisle, and Kabbani 2001; Entwisle, Alexander, and Olson 2005). Research on the predictiveness of elementary school grades is mixed, with about half of studies finding insignificant relationships and half finding significant relationships, after including demographic covariates (Ensminger and Slusarcick 1992; Ensminger, Lamkin, and Jacobson 1996; Entwisle et al. 2005; Finn, Gerber, and Boyd-Zaharias 2005). At this early age, researchers often focus on the effects of grade retention. They overwhelmingly find a negative association between being 'held back' in early grades and high school graduation

(Alexander, Entwisle, and Dauber 2003; Alexander et al. 2001).

The little research on early attitudes and behaviors are discussed in Noncognitive Traits and High School Graduation. Other early predictors of high school graduation include residential mobility, family change, and parental mental health, education, and parenting practices (Barnard 2004; Clements, Reynolds, and Hickey 2004; Ensminger et al. 2003; Finn et al. 2005; Haveman, Wolfe, and Spaulding 1991; Pollak and Ginther 2003). Overall, however, the influence of early factors on high school graduation is poorly understood.

Noncognitive traits

Investigating the factors that contribute to high school dropout is embedded in the larger discussion of the origins of unequal outcomes, particularly why parents' outcomes seem to be so closely related to those of their children. Psychologists Herrnstein (1973) and Jensen (1973) both argued that unequal outcomes develop from differences in intelligence, the levels of which are fixed and passed genetically through generations. There is, in fact, evidence of a relationship between genetic inheritance of intelligence and outcomes ranging from educational attainment to labor market success (Herrnstein and Murray 1994). Yet a more nuanced interpretation of systematic inequality has emerged that takes into account factors that are not purely intelligence-based, at least in the traditional sense. This simple idea sparked a vibrant research tradition on the intergenerational reproduction and the effects of these characteristics.

Yet the idea that factors other than intelligence can affect outcomes is not new. As Camic (1986) points out, the concept of habit has been important to sociology since its conceptual beginnings in Durkheim and Weber. To Durkheim, habit was the most significant factor influencing human behavior, and he believed that the moral framework of a society is supported by habitual action. Weber placed habit centrally in his understanding of the spirit of capitalism and traditionalism. During the course of the twentieth century, Camic (1986) argues, the theme of habit fell victim to the institutionalization of sociology as a discipline. In this way, the present study is part of a larger movement to reclaim what was once obscured in the field of sociology.

Of course, the study of habitual action is not unique to sociology. Psychologists, for example, have long studied non-intellectual characteristics under the classification of traits or cognitive and emotional self-regulation (for one introduction to an enormous field, see Eccles and Wigfield (2002)). Economists, in contrast, conceive of this broad skill set generally as "noncognitive" skills (this arguably began with Bowles and Gintis (1976), but the field is today led by James Heckman). Despite wide-ranging theoretical and nominal distinctions between and within disciplines, there is a broad agreement that these factors have a profound influence on individual educational outcomes.

Marxian economists Bowles and Gintis (1976), responding to Herrnstein (1973) and Jensen (1973), argued that inequality is not passed down genetically, but through modes of behavior, or what they interchangeably refer to as "noncognitive," "personality," or "behavioral" traits. Schools, they argue, promote the types of behavior that are valued by employers, and, more broadly, that will facilitate a smooth transition into the workforce when students are finished with formal schooling. This, they argue, is fueled at an aggregated level by the hierarchical arrangement of power in the school, but also at a lower level by promoting the development of skills that reflect the behavioral requirements of roles in the division of labor. At each stage of schooling, students are taught a new form of behavioral regulation; even within the same year, curriculum tracking reflects levels in the industrial model of the division of labor. The strain of thinking introduced by Bowles and Gintis has arguably sparked our modern conceptualization of noncognitive traits or skills as an instrument shaping outcomes.

The exact nature of noncognitive traits is not easy to pin down. The term itself is framed as a negation of cognitive traits, yet the characteristics undoubtedly have cognitive components, and also contribute to the results of assessments of those traits traditionally considered 'cognitive.' Indeed, noncognitive traits form a theoretically and analytically amorphous group of characteristics that has, in the literature, referred to everything from attitudes to attendance, leadership to like-ability. I take a somewhat agnostic approach to the problem of definition. I use 'noncognitive traits' to refer to those skills and habits not directly evaluated in most American academic environments. Noncognitive traits therefore stand in contrast to language examinations, mathematic examinations, evaluations of scholastic aptitude or ability, or knowledge of any particular subject area. Noncognitive traits, as I use the concept, are the characteristics that mediate an individual's relationship with the social world, both in terms of attitudes towards their environment and environmental stimuli, as well as their behaviors within this environment. In sum, I use noncognitive traits to refer to 'social and behavioral skills and characteristics.'

Much scholarship has studied specific characteristics that fall under the wide-ranging category of noncognitive traits. By using a very broad definition of noncognitive traits, a minor aim of this paper is to evaluate the analytical and theoretical utility of a generalized concept of noncognitive traits.

Several models have emerged for understanding the (non-genetic) mechanisms by which skills develop in the context of the family and society. Human capital theory, for example, originally laid out by Becker (1964), argues that individuals learn skills through education necessary to complete tasks more efficiently, and their wages reflect this increased efficiency. In this paradigm, parents and social institutions invest time and effort in teaching children skills, choosing selectively what skills are worth passing down based on a cost-benefit analysis. Originally, the human capital paradigm focused largely on cognitive skills. Recently, it has grown to incorporate noncognitive behaviors as well (see Bowles and Gintis (2000) for a somewhat standard treatment).

Another model operates through cultural capital (Swidler 1986). In this perspective, some families fail to adequately prepare their children because they have limited access to the skills and habits they would need to do so (Farkas 2003). A third model takes a similar perspective, but emphasizes social capital rather than cultural. Instead of lacking access to the skills and habits that are necessary to teach their children, in this paradigm families lack resources that accrue through social networks.

All three of these models take as their starting points differential investment by families, either by choice or by inability. Yet there is another force at work that shape stratification processes: institutions. There is a bidirectional relationship between investments and institutions, such that investments made early in a child's life influence the institutional opportunities available to them at a later time, which in turn shape the way that they interact with institutional structures. A student who arrives at school cognitively or behaviorally unprepared has fewer opportunities available to him or her, which in turn shapes the way the student behaves within this environment. ("Why should I bother trying? Even if I become great at math, I will never be placed in the advanced classes.") In this way, early levels of noncognitive traits have important, long-lasting implications, and interventions staged at early moments in the student's life can have enormous influence on outcomes later in life.

Noncognitive traits and high school graduation

It is well documented that various noncognitive traits are associated very strongly with high school graduation, even after controlling for cognitive ability levels. The General Educational Development (GED) exam and other high school equivalency exams have proven among of the most fruitful ways to study the association between noncognitive traits and high school graduation. In their landmark study, Cameron and Heckman (1993) find that despite their nominal equivalence, recipients of GEDs experience the labor market outcomes more similar to high school dropouts than high school graduates, when controlling for the opportunities afforded by the GED certification, a finding they attribute to differential levels of noncognitive skills among the types of people who get GEDs and the types of people who graduate normally. Subsequently, Heckman and Rubinstein (2001) find that while GED holders are cognitively equivalent to high school graduates and have higher cognitive ability than other high school dropouts, they tend to have lower levels of noncognitive skills than high school graduates and similar levels to dropouts. The message is clear: something other than cognitive ability influences chances of high school graduation.

The work of many other scholars sits alongside Heckman's work to paint a reasonably thorough picture of the relationship between levels of noncognitive traits among high schoolers and their prospects for high school graduation. We can first consider those noncognitive traits that can be characterized as behaviors. One such behavior is 'engagement,' a broad category encompassing a student's level of involvement with both class work (for example, preparedness for class, homework completion, or attendance) and social activities (for example, sports or extracurriculars). Though operationalized in many ways, there is a general consensus that higher levels of engagement in high school are associated with higher odds of graduation (Rumberger and Lim 2008). These patterns hold for analyses that use generalized operationalizations of engagement and more specific ones, such as absenteeism or extracurricular activities. Another predictive behavior is deviant activity, such as delinquent behavior within and outside of school or alcohol and drug use. Most research focuses on specific deviant behaviors as predictors of dropout, but some use statistical constructs of deviant behavior. These studies collectively indicate that higher levels of deviant behavior are predictive of high school dropout, and this is true of both middle school and high school behavior. Additionally, being friends with people who engage in deviant behavior is a factor associated with high school dropout.

Other than behavior, attitudes (such as motivation, goals, or self-confidence) are noncognitive traits that have a relationship with the odds of high school graduation. Most studies attempting to understand the role of attitude study specific attitudes, rather than attitudes more broadly understood (Rumberger and Lim 2008). A notable and enlightening exception is Alexander et al. (2001). Using a life-course approach to study a cohort of Baltimore public school children, the researchers combine a number of survey items to create a single attitudinal construct for each individual at four different points in the student's childhood. This allowed them to understand how the relative and overall effects of certain variables change over the course of childhood. They find that engagement (a behavioral characteristic) is a statistically significant predictor starting in first grade, even after controlling for educational performance and socioeconomic background, but that the attitudinal construct does not produce its own significant effect until grade nine. Even then, the effect of behavior is stronger.

Alexander et al. (2001) is a unique and important paper in another way, as well. Much like the literature on high school graduation, the literature on noncognitive traits and high school attainment is dominated by studies using predictors measured later in childhood—typically junior high and high schools. As we have discussed, understanding early predictors is also important from both a theoretical and policy perspective.

Alongside Alexander et al. (2001), a small handful of studies take this long view when trying to understanding the relationship between noncognitive traits and high school graduation. One such study is Ensminger and Slusarcick (1992). The researchers study a cohort of first graders in a school district in Chicago, with data collected from district records throughout childhood and adolescence, capturing a number of individual characteristics, grades, and graduation status. They find that while certain types of behavior (particularly aggression) are important predictors in first grade of later high school graduation, attitude is not. In particular, they find that these behaviors have pure direct effects, and their interactions with background characteristics have effects that are both direct and indirect. They also find that the results differ between males and females, shaping the resulting path analysis.

Relatedly, in their longitudinal study of neighborhood effects and high school graduation using the same Chicago dataset, Ensminger et al. (1996) operationalize the concept of situational vulnerability through the interaction of early attitudes and behaviors (school performance and aggressive behavior) and neighborhood. They do not find a relationship between this variable and high school graduation.

Another significant—and relatively recent—contribution to the literature on the long-term relationship between early noncognitive traits and high school graduation is Entwisle et al. (2005). Studying a sample of Baltimore public schoolchildren, they find that socioeconomic status and noncognitive factors (which they operationalize as "temperament/disposition") in first grade are significant predictors of high school graduation, even more so than gender or race. Their paper, though focused more broadly on educational attainment, offers striking and illuminating insight into the relationship.

This paper aims to address some of the less explored areas in the high school graduation literature. First, it takes a process-based view of high school graduation that takes into consideration demographic characteristics, early noncognitive traits, adolescent behaviors, and finally high school graduation. This approach separates the present paper from much of the high school graduation literature, which focuses on short-term predictors. Second, unlike many studies on what might be identified as noncognitive traits, it utilizes a single noncognitive construct, which encompasses both behavioral and attitudinal characteristics. This study then allows us to begin examining the usefulness of a single noncognitive construct, as distinct from specific attitudes and behaviors. Third, I use a nationally representative dataset, while most prior research focuses on data from a single city or school district. This may allow for a stronger statistical control for situational characteristics.

The paper unfolds as follows. I first present the dataset upon which I base this study, during which I address the problems of substantial missingness and constructing a generalized measure of noncognitive traits. In the following section, I present the results of analyses uncovering three aspects of the connection between early noncognitive traits and high school graduation: the strength of the *relationship*, both adjusting and not adjusting for demographic covariates; the role of later behavioral patterns in *mediating* this relationship; and the role of certain individual characteristics in *moderating* the relative importance of noncognitive traits in predicting high school graduation. I conclude by outlining the empirical and theoretical implications of the results, as well as suggesting areas for further investigation.

Data and Methods

This study is based on data compiled from the public-use portions of the Panel Study of Income Dynamics (PSID), a national longitudinal study based at the University of Michigan that began in 1968. In addition to data from the main interview, I utilize data from the Child Development Supplement (CDS) and the Transition into Adulthood (TA) studies. CDS collects information on the children (aged zero to twelve in 1997) in PSID families, with a particular emphasis on their physical, cognitive, and social conditions at home and at school. TA is an extension of CDS that reconnects with the same individuals after they have turned eighteen and no longer attend high school. It seeks to understand the economic and social conditions of young adults as they move towards economic and social independence.

This dataset has a number of advantages for the present study. First, it makes available high quality background information on the children's personal characteristics and family conditions, allowing for a more nuanced and insightful analysis of the influence of childhood levels of social and cognitive traits on high school persistence through carefully constructed controls, and for a high-fidelity analysis of how different types of demographic variations moderate outcomes. Second, the structure of TA allows for the most complete collection of information about high school graduation status, as individuals reenter the cohort soon after their high school education status is fixed, reducing the risk of study dropout. While the PSID is a common dataset for exploring factors associated with high school graduation (in their extensive survey of the high school dropout literature, Rumberger and Lim (2008) find that it is the third most frequently used dataset), it appears to have never been used to study the relationship between noncognitive skills and high school graduation. What's more, the non-cognitive measures collected in the Child Development Supplement have apparently never been used in a major peer-reviewed journal article. Rich background information and lack of previous research on this dataset make it ideal for this study.

The sample consists of those children in CDS families who were between first and sixth grade in 1997 ($n = 1809$). The graduation rate for the sample was around 80%.[1]

Noncognitive traits

I am primarily interested in the noncognitive trait characteristics of the students early in their education. To measure these, I use the results of a twenty-item subsection of the teacher questionnaire of the CDS. Each question asked the teacher to indicate their level of agreement with statements regarding the behavioral and attitudinal characteristics of a student on a scale of three. The

[1] Note that summary statistics are somewhat misleading because of the imputation procedure described below. This value is the average across the imputed datasets.

battery of questions is based on the Achenbach Behavior Problems Checklist, designed to assess behavioral problems in a survey setting.

The twenty measures together constitute a single latent variable in the analysis, a very broad operationalization whose value we would like to evaluate. The noncognitive score was constructed using factor analysis with a one-factor solution. Because factor rotations are arbitrary, the loading matrices for the imputed datasets were rotated using Procrustean rotation to align the solutions with an arbitrarily-defined reference loading matrix (here, that of the first imputed dataset). The adequacy of the one-factor solution is taken as a non-trivial assumption in the present study for reasons discussed in Noncognitive Traits and High School Graduation. The scores are then standardized within each of the imputed datasets.[2]

Independent variables

Additionally, a number of independent variables were chosen to control for other potential relationships between the variables of interest. Race, gender, and grade level were collected as individual-level demographics. Household-level demographic variables include parental high school completion, household structure, and size-adjusted household income (smoothed over the time period from 1994 to 2001). Note that because of the survey structure, parental high school graduation status was carried forward using the algorithm suggested in the dataset documentation. To measure cognitive skills, the results of a standardized letter-word recognition assessment were collected. All of these background variables were collected during Wave I of the CDS.

Several variables were also collected to evaluate as potential pathways through which early noncognitive traits might operate to to contribute to graduation or dropout. These variables, which measure demographic characteristics during high school, were collected in TA. They include high school grade point average (which was rescaled and normalized using information reported by the student), a measure of academic performance, and the frequency of problematic behavior in the previous six months, including number of times damaged school property, number of times parents called into school for misbehavior, and number of times skipped school without permission. Note that all of these variables are subject to reporting bias and misremembering.

[2]Another reasonable strategy for estimating this latent variable would have been simultaneous estimation procedures such as those in generalized structural equation models. I explored this possibility, but did not pursue it because of the lack of tools for carrying out these calculations and the prohibitively involved programming needed to implement it appropriately for this dataset.

High school graduation

The dependent variable, high school completion, is available in TA. Because the members of the cohort enter TA in different years, results from the three available years (2005, 2007, 2009) are carried forward. Some individuals do not have graduation status available in any of those three years, presumably because of attrition or because they did not meet one or more of the selection criteria by the year 2009. These values are imputed. Because of the research on GED earners and life outcomes (see Noncognitive traits and high school graduation), GED or other high school equivalency earners are coded as dropouts.

Missing data

The data exhibit significant missingness, particularly due to nonresponse from teachers. Understanding the pattern of missingness will allow us to develop a rigorous approach to the missing data. We will use the typical characterizations outlined by Rubin (1976). First, note that there is no reason to suspect that the data are missing completely at random (that is, missing with no relationship to any variable, observed or not); in fact, we may expect this not to hold, given that the school environment likely has an effect on the teacher response rate. As such, case deletion is not a reasonable strategy for addressing the missingness. Missing at random is at least an intuitively defensible assumption for these data. It is not clear, for example, that teacher non-response is related to the characteristics of the students (or the relationship may be dwarfed by the relationship between non-response and teacher personality). That being said, there is also a case to be made that the data are missing not at random. For high school graduation status, for example, the probability of nonresponse may be closely tied to graduation status—perhaps it is harder to follow-up with individuals who dropped out of high school. Unfortunately, we have no better recourse for understanding the structure of the missingness than speculation. Thus, we will proceed under the assumption that the data are missing at random.

Multiple imputation is a technique well suited to the present dataset. The general strategy is to impute a case's missing values on the basis of the non-missing values in a way that maintains the relationships between the variables observed in the complete cases. This probabilistic process is carried out several times to form a number of slightly different simulated datasets. All statistical procedures are then run on each of the datasets and combined using the techniques outlined in Rubin (1987), adjusting the standard error to account not only for the variability of the statistic itself, but also the variability introduced by the imputation. If the observed values are only weakly related to the missing values, there is more imputation variability, leading to larger standard errors and weaker conclusions. Multiple imputation allows us to maximally utilize the available information while appropriately accounting for the variation we introduce by doing so.

To carry out the imputation, I use the *mi* package in R, which implements the multiple imputation through chained equations (MICE) algorithm. The MICE algorithm iteratively estimates missing values, builds regression models for the missing values based on the estimates, and estimates again, for a set number of iterations. This process is repeated for each of the datasets generated. The approach is notable for its flexibility and the variety of statistical software implementing the approach. MICE formally assumes missing at randomness (Azur et al. 2011).

Given the high levels of missingness in this study, and following the simulated findings of Graham, Olchowski, and Gilreath (2007), I generate forty datasets. Thirty iterations were run for each dataset, which yielded satisfactory (though non-convergent) estimates as judged by the diagnostic plots (not reproduced here). The imputation model included all of the variables in the main analysis, along with parental assessments of noncognitive traits. For the most part, variables were not transformed prior to the imputation procedure (for example, each item from the teacher noncognitive traits assessment is imputed separately, rather than the summary data). Declined responses were coded as missing and imputed. Because of the computational intensity of this task, it was carried out on an Amazon Elastic Compute Cloud server generously funded by the Columbia College senior thesis fund.

The resulting imputed datasets were exported from the imputation server and analyzed locally using mostly custom-written code in R. The code is freely available on GitHub. Please note that because of the usage agreement with the PSID, I am unable to distribute the data. Code for the multiple imputation procedure is included if the reader would like to replicate the results.

Results

Relationship

I first analyzed the predictive power of noncognitive traits, measured between first and sixth grade, for high school graduation, without controlling for other characteristics. This was accomplished using a simple logistic regression with graduation as a response variable and the noncognitive score computed through factor analysis. For comparison, similar regressions were fit using cognitive skill levels and standardized size-adjusted household income as the independent variable. The results, summarized in table 1, suggest that noncognitive traits are related to high school graduation at levels similar to cognitive skills, both of which are much less predictive than household income. While a one standard deviation increase in noncognitive traits is associated with a graduation odds increase of 1.61 times ($p < 0.001$), this same value for cognitive skills is 1.64 times ($p < 0.001$), and 3.38 times ($p < 0.001$) for household income.

When including demographic controls (race, sex, household income, mother's education level, and household structure), the estimate for noncognitive traits remains largely unchanged. The same, however, is not true of cognitive skills, whose influence drops out of statistical significance. The insignificance of early cognitive test assessments is consistent with much of the literature, but the significance of noncognitive skills is a unique finding in an under-explored field (Alexander et al. 2001; Ensminger and Slusarcick 1992). For the full regression statistics, as well as the formal model, see the appendix.

Factor	Graduation Odds Ratio (uncontrolled)	Graduation Odds Ratio (controlled)
Noncognitive Traits	1.61	1.35
Cognitive Skills	1.64	(NS)
Household Income	3.38	

Table 1: Odds ratios for graduation associated with one standard deviation increase in factor.

Pathways

I next investigated possible mechanisms through which non-cognitive traits may have operated in leading towards graduation or dropout. Here, I use a very simple path conceptualization, as shown in the path diagram below. From a theoretical standpoint, I selected two possible pathways: academic performance and student behavior. To operationalize the first variable, I used high school grade point average, as reported by the student, rescaled to a percentage. To operationalize student behavior, I used three measures of behavior:

- number of times in the last six months damaged school property
- number of times in the last six months parents were called into school because of misbehavior
- number of times in the last six months skipped school without permission

The path analysis is slightly complicated by the mixture of models necessary in this situation. The outcome is dichotomous, while the behavioral measures, being counts, are Poisson distributed, and the academic measure, being continuous, is presumably Gaussian distributed. I also include controls for the vector of demographic variables previously mentioned. See Appendix B for details on the models. To carry out the path analysis with these many probability structures, I use the R package *mediation*, which uses bootstrap sampling to estimate confidence intervals and p-values for the size of the direct and indirect effects estimates. The procedure indicates that neither high school GPA nor any of the problem behaviors mediate the relationship in any meaningful way.

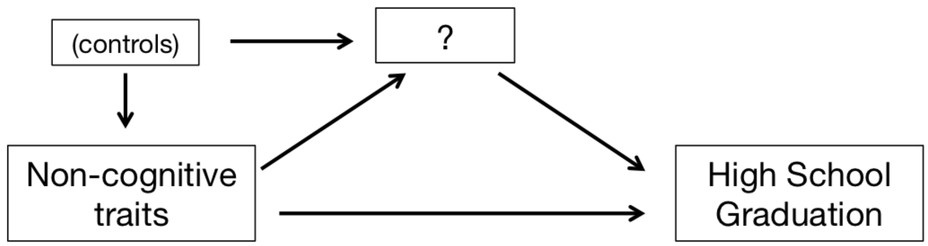

Figure 1: Path Diagram

This is an unintuitive result. Inspecting manually the constituent models in the mediation analysis calls into question the quality of the data. For example, high school GPA, when controlling for demographic characteristics and noncognitive traits, has a slightly negative effect on the odds of graduation ($estimate = -0.45; odds = 0.63$). The estimate, however, is dwarfed by its standard error, whose magnitude is more than four times the size of the estimate (1.67). This suggests that the quality of the data is very low, or that the imputation procedure added too much noise to detect a signal. Another possibility is that the models inadequately reflect the nature of the relationship. Of course, the lack of conclusive results could also reflect a reality that there is no underlying relationship between these variables.

Regardless, based on these data, we can conclude that if the students drop out because of their noncognitive traits, it is not because these traits led them to get bad grades, nor because it led them to behave poorly in school. Alternative pathways and further interpretation of these results are discussed below.

Decomposition

Another question we may ask ourselves is whether the effect of noncognitive traits on high school graduation acts uniformly for all members of the population. Although levels of noncognitive traits vary across different subpopulations, one might speculate that they have unequal influence on each of them. For example, women, in general, have higher levels of noncognitive traits. Though this works in favor of women as a group, it might also make their environments less tolerant towards deviations from this norm, ultimately making the trait more important for outcomes. I analyzed the potential moderating effects of race, gender, and household income.

To model this relationship, I used two strategies. First, I added a simple interaction term between noncognitive traits and the variable of interest and tested the statistical significance of the estimate for the coefficient of this term. Next, I used a decomposition approach in which separate models are fit for each of the subsamples. (Note that this second strategy is statistically equivalent to modeling interactions between the variable of interest and all other variables in the model.) The coefficients for noncognitive traits in these two decomposed models were then compared by subtracting them and standardized by their pooled standard error. This, in conjunction with the fact that they are distributed approximately normally, can be used to construct confidence intervals.

The results of these two strategies are summarized in tables 2 and 3. While the findings suggest some modest differences in the importance of non-cognitive traits between the groups, particularly gender (which suggests that being female makes noncognitive traits somewhat more important), none of the differences in either of the two models show these results to be statistically significant. On the basis of these results, we conclude that these data provide no evidence that the importance of noncognitive traits differs between different subpopulations.[3]

Interaction with	Estimated Odds Ratio	p-value
Sex (female)	1.27	0.098
Race (nonwhite)	1.25	0.81
Income	0.97	0.85

Table 2: Decomposition Strategy 1

Interaction with	Group	Coefficients (SE)	p-value
Sex	Female	0.35 (0.10)	0.29
	Male	0.20 (0.10)	
Race	White	0.23 (0.12)	0.60
	Nonwhite	0.31 (0.10)	

Table 3: Decomposition Strategy 2

[3]An extension of this approach would be to construct a small number of 'advantage' groups based on a few salient characteristics, and then compare the coefficients for these groups. This strategy is used fruitfully by Lundberg (2013) to study the differential importance of certain specific personality traits on college completion for different advantage groups. Unfortunately, because of time constraints, I am unable to carry out such an analysis.

Discussion and Conclusion

Empirical implications

Perhaps the most significant finding of this paper is that, when using early measures to predict later high school graduation, noncognitive characteristics remain significant after comparing for important demographic covariates, while cognitive aptitude does not. The finding for cognitive measures appears to be well-established in the literature (Rumberger and Lim 2008). The finding for noncognitive measures is in line with findings in Alexander et al. (2001), which suggest that early behavioral measures are predictive of high school graduation, even after controlling for important covariates. It is also consistent with Entwisle et al. (2005). This growing consensus has important policy implications. Much of the educational reform movement focuses on improving cognitive outcomes. While gaining cognitive ability is one important outcome of schooling, this paper suggests that in the long run, focusing exclusively on cognitive development may not help other important outcomes, such as high school graduation.

Somewhat counterintuitively, there is also an argument to be made for focusing on noncognitive traits in order to improve cognitive outcomes, an indirect pathway largely unexplored in public policy. Insofar as noncognitive traits allow students to learn content more effectively, intervention programs that focus on improving noncognitive skill sets may also improve cognitive outcomes, alongside benefits in other areas, including high school graduation. Though this relationship is not explicitly explored in this article, it remains an important consideration that should be explored further.

One aspect of the relationship between noncognitive traits and high school graduation that remains unexplored in this paper is that of neighborhood effects, which may be a strong confounding variable (Ensminger et al. 1996). Unfortunately, this study was unable to incorporate location data because most of this information is available only in the restricted-use dataset, which I discovered too late to undergo the approval process with the institutional review board. Incorporating this information into the model is an important extension of the present study.[4]

This paper was unable to show that academic performance or troublesome behavior act as causal pathways through which noncognitive skills act to influence dropout. On the basis of these findings, we are left to conclude that the effect may be direct. In other words, it could be that the general day-to-day existence

[4]I would like to thank Christina Ciocca for this suggestion. I would also like to take the opportunity to suggest a possible response. One could argue that the noncognitive scores do, in some sense, control for neighborhood characteristics, as teachers presumably evaluated the students *in comparison to* the other students in the neighborhood. In this view, the measures for each student are relative to his/her environment, which controls for variation in environment. Testing this claim is challenging and beyond the scope of this paper, but it is worth mentioning.

of students with low noncognitive traits leads to dropout, rather than leading to other outcomes to lead to dropout. It could be the general lack of motivation, difficulty getting along with others, short-term orientation, or any number of other noncognitive traits that led dropout.

Yet it is hard to imagine that the direct effect is the only relationship between noncognitive traits and high school graduation. There are surely pathways through which these traits operate. One possibility is that the characteristics I investigated as potential pathways are, in fact, pathways, but our data are not high enough quality to demonstrate this. Access to school records, rather than subject self-reports, would significantly improve the quality of the data, as well as introduce variables that are unavailable in the PSID but are likely to act as a pathway, such as attendance.[5]

The path analysis in this study makes the crucial assumption that noncognitive characteristics remain at least somewhat consistent over time. The reasonableness of this assertion is not entirely clear. If noncognitive characteristics do not remain constant over the years, however, then the conceptual model of pathways utilized in this paper begins to break down, which would explain the lack of evidence for these particular pathways found in this paper.

The decomposition analysis did not lead us to conclude that the predictive power of noncognitive skills differs within different subpopulations, after controlling for other demographic characteristics. Two points should be made about these findings. First, this does not imply that policy interventions should not target particular populations. Indeed, we observe vastly different levels of noncognitive skills in the population among different groups, which suggests that certain groups are systematically disadvantaged in the acquisition of noncognitive skills. As such, although noncognitive traits appear to be equally important for males and females (for example), males, on average, have lower levels of noncognitive traits, meaning that policies should perhaps focus on young men, rather than young women, in boosting noncognitive traits.

Second, it is very possible that the importance of noncognitive traits varies between different contexts, so a decomposition on the basis of neighborhood-level variables might yield important and socially significant results. Again, because of restricted access to neighborhood information in the sample, this route remains largely unexplored.

Theoretical and methodological implications

I began with the assertion that viewing dropout as a process, rather than an event, has theoretical value, but that this perspective has remained largely unexplored in the empirical literature. My findings demonstrate that there is also analytical value to this conceptualization, and that it allows researchers to make

[5] I would like that thank Professor Thomas DiPrete for suggesting this pathway.

important insights about the long-term effects of early characteristics. Though this broader point—that events early in life can influence the pathways through which life events unfold—is perhaps not a profound one, it appears particularly underrepresented in the literature, especially with regard to understanding the relationship between noncognitive traits and high school graduation. This paper serves as a subtle reminder that the academic consensus sometimes overlooks, to its detriment, commonplace conceptions about the social world.

This paper also has methodological implications. It demonstrates that, although the PSID was not designed for studying noncognitive traits, it has some value for studying its effects. Further, it has demonstrated that, although the teacher responses in the CDS suffer from substantial missingness, some conclusions can be drawn from this dataset for the study of noncognitive traits and other such characteristics after a multiple imputation procedure on the dataset.

It is worth noting, however, that the data also render questionable the usefulness of teacher evaluations of noncognitive traits. There is a heavy skew in the responses towards perfect scores, which could suggest a number of possibilities. First, it is (ironically) possible that teachers were themselves not particularly diligent in filling out the responses, and so did not consider very closely the questions being asked. Second, it could suggest that the three-point scale does not provide enough fidelity for the teachers to give an accurate assessment. In either case, it might be wise to take the ratings with a grain of salt, and to redouble efforts on analyzing data with strong measures of these characteristics.

Finally, this study also demonstrates the apparent utility of a generalized statistical construct for noncognitive traits. The very broad conceptualization of noncognitive traits used in this paper could easily have proven useless if it tried to simultaneous capture too many conflicting factors. Though this paper makes no attempt to identify a noncognitive equivalent of a 'g factor' in psychometric research, it demonstrates that there is at least some empirical value to constructing a generalized noncognitive measure.

Areas for future research

This study leaves several open research questions. First, the finding that noncognitive traits at an early age are predictive of high school graduation, controlling for demographic variables, while cognitive skills are not, is one that could use further investigation. The scientific consensus for such a finding might emerge if it is demonstrably robust to operationalizations of noncognitive traits and particular datasets.

Further, the nature of the causal pathways through which noncognitive skills operate leading up to high school graduation remains an open question. While I found no evidence that the particular measures used for academic performance and troublesome behavior act as a pathway, it is possible (likely, even) that these variables do, in reality play a role. Thus, future studies might use other measures of these concepts to study the question again. They also might address the large assumption that noncognitive traits remain stable by building more complicated pathways that take into account intermediary effects and longitudinal variability in noncognitive traits.

Finally, future research could focus on identifying specific noncognitive traits at this early age that are especially predictive of later high school graduation. Such work would not only help public policy-makers target their efforts in the most effective ways for achieving desired aims, but would also suggest possible mechanisms through which noncognitive traits might act.

Conclusion

Using data from the PSID, this study has shown that noncognitive traits, when measured early, are predictive of high school graduation, even when controlling for important demographic variables. The same is not true of cognitive traits. It also found no evidence that poor academic performance or troublesome behavior act as mediating variables in this relationship, nor that the magnitude of the relationship between noncognitive traits and high school graduation differs between different subpopulations. This study also demonstrates the theoretical and analytic value of understanding high school graduation or dropout as a process, not an event, and the construction of a generalized noncognitive trait.

In the broader social context, this article serves as an indictment of the educational reform movements focused primarily on improving cognitive outcomes in American public schools. Although learning content and becoming a better thinker are undoubtedly important outcomes of education, perhaps even more important are the skills and perspectives you gain that you will bring with you for the rest of your life.

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Appendix

Note that all of these models below were fit to each of the multiply imputed datasets, and the results are combined as discussed in the paper. All statistics below represent these combined results.

1 Relationship

I here present the extended methodology for the relationship analysis, as well as the results of the regression analysis.

1.1 Simple relationship

The simple relationship between various predictors and high school graduation was modeled as

$$logit(\pi) = \beta_0 + \beta_1(X) + \epsilon,$$

where

- π is the probability of graduation from high school,
- X is the variable of interest,
- and ϵ is an error term (for the sake of brevity, this is the only time I will mention this term).

1.2 Controlled relationship

I then modified the regression model to incorporate important potentially confounding covariates:

$$logit(\pi) = \beta_0 + \beta_1(sex) + \beta_2(race) + \beta_3(income) + \beta_4(familyEduc) + \beta_5(householdStructure) + \beta_6(noncognitive) + \epsilon,$$

where

- π is the probability of graduation from high school,
- *sex* is a binary variable ($1 = male, 2 = female$) indicating the biological sex of the child, and
- *race* is a categorical variable indicating the reported race of the child,
- *income* is size-adjusted household income, smoothed available data between 1994 and 2001,
- $familyEd$ is a binary variable denoting the biological mother's high school graduations status,
- *householdStructure* is a categorical variable denoting the presence of biological family in the home (larger is worse),
- and *noncognitive* is the noncognitive score, computed as described in the study.

From here on, denote the vector of demographic covariates described above (everything except for *noncognitive*) $\mathbf{X}$.

1.3 Full Results

The full results are summarized in the table below.

Regression models for relationship section					
	(1)	(2)	(3)	(4)	(5)
(Intercept)	1.46*** (0.069)	1.44*** (0.068)	1.65*** (0.090)	1.22*** (0.27)	1.16*** (0.27)
Noncognitive Traits	0.47*** (0.062)			0.30*** (0.074)	
Cognitive Skills		0.49*** (0.10)			0.13 (0.11)
Household Income			1.22*** (0.17)	0.79*** (0.19)	0.79*** (0.19)
Sex (Female)				0.39*** (0.15)	0.51*** (0.15)
Race: Black				-0.17 (0.19)	-0.20 (0.18)
Race: Other				0.25 (0.30)	0.26 (0.30)
Family Structure				-0.36*** (0.10)	-0.39*** (0.10)
Mother's Education				1.21*** (0.23)	1.26*** (0.23)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2 Mediation

I here present extended methodological details for the mediation analysis. The simple path analysis involved fitting two models:

- noncognitive traits and demographic controls are used to predict the mediating factor
- noncognitive traits, demographic controls, and the mediating factor are used to predict the outcome (high school graduation).

As I mention in the main article, because of the flexibility needed in this particular case and the computation concerns introduced by the imputation, I opted to use a bootstrap-based estimation method implemented in R. As such, I do not present parameter estimates for the fitted models of the individual regressions.

The general models were as follows. For predicting the behavioral measures as mediating variables,

$$log(E(b)) = \beta_0 + \boldsymbol{\beta}(\mathbf{X}) + \beta_n(noncognitive) + \epsilon,$$

where

- $log(E(b))$ is the log of the expectation of the count of event b (problematic school behavior),
- $\mathbf{X}$ is the vector of demographic controls,
- and *noncognitive* is the noncognitive score.

Again, this is modeled as Poisson. For predicting academic performance as the mediating variable, the model is simpler:

$$gpa = \beta_0 + \boldsymbol{\beta}(\mathbf{X}) + \beta_n(noncognitive) + \epsilon,$$

where

- gpa is high school GPA,
- $\mathbf{X}$ is the vector of demographic controls,
- and *noncognitive* is the noncognitive score.

For both of these models, the model for predicting the outcome was as follows:

$$logit(\pi) = \beta_0 + \boldsymbol{\beta}(\mathbf{X}) + \beta_{n-1}(mediator) + \beta_n(noncognitive) + \epsilon,$$

where

- π is the probability of graduating from high school,
- $\mathbf{X}$ is the vector of demographic controls,
- *mediator* is the mediator being analyzed, either counts of misbehavior or GPA,
- and *noncognitive* is the noncognitive score.

3 Decomposition

As mentioned in the study, I used two strategies for decomposition: interaction terms and separate regressions.

3.1 Interaction terms

For the interaction terms, the following model was used:

$$logit(\pi) = \beta_0 + \boldsymbol{\beta}(\mathbf{X}) + \beta_{n-1}(noncognitive) + \beta_n(noncognitive * f) + \epsilon$$

where

- π is the probability of graduation from high school, and
- $\mathbf{X}$ is the vector of demographic covariates described above, and
- *noncognitive* is the noncognitive score, and
- f is the factor of interest (one of the measures in $\mathbf{X}$)

The results of these models are presented in the table below.

Regression models for decomposition (method 1)			
	(1)	(2)	(3)
(Intercept)	1.19*** (0.27)	1.23*** (0.29)	1.23*** (0.27)
Noncognitive Traits	0.22** (0.090)	0.16 (0.20)	0.29*** (0.09)
Household Income	0.79*** (0.19)	0.79*** (0.20)	0.79*** (0.19)
Sex (Female)	0.43*** (0.15)	0.40*** (0.15)	0.39*** (0.15)
Race: Black	-0.18 (0.19)	0.40** (0.17)	-0.17 (0.19)
Race: Other	0.24 (0.30)	-0.16 (0.26)	0.25 (0.30)
Family Structure	-0.36*** (0.10)	-0.37** (0.15)	-0.37*** (0.10)
Mother's Education	1.21*** (0.23)	1.21*** (0.22)	1.21*** (0.23)
Noncognitive*Fem	0.24* (0.15)		
Noncognitive*Race		0.22 (0.94)	
Noncognitive*Income			-0.029 (0.15)

* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01*

3.2 Separate regressions

For the separate regressions, the following model systems were estimated:

$$logit(\pi) = \beta_0 + \boldsymbol{\beta}(\mathbf{X}^{-}{}_{group1}) + \beta_n(noncognitive_{group1}) + \epsilon$$

and

$$logit(\pi) = \beta_0 + \boldsymbol{\beta}(\mathbf{X}^{-}{}_{group2}) + \beta_n(noncognitive_{group2}) + \epsilon,$$

where

- π is the probability of graduation from high school, and
- $\mathbf{X}^{-}$ is the vector of demographic characteristics, without the entry for the groups analyzed by each model, and
- *group* designates the subset of entries upon which the model is run.

Note that I did not analyze using this strategy, as it is not necessarily logical to split it into discrete groups. Although I could have fit the statistically equivalent model with all of the interaction terms between income and the other variables, on the basis of the lackluster from the previous analysis, I decided to forgo this option.

For efficiency, the results of this approach is presented in the body of the text.